Development of Direct Digital Control For Ethanol Fermentation Process

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Abstract

In any process, good production rate, high purity product, efficient and safe operation can not be guaranteed unless a good process control system is installed. However, in developing a sensitive process control scheme, accurate process description is required. This is particularly difficult in biological processes because the dynamics are normally non linear, nonstationary and time varying. One approach to this class of problem is by employing recursive estimation techniques and this paper will illustrate its application on ethanol fermentation. The study started with simulation works and actual experimental activities are under formulation.

Introduction

The main problem in controlling bioreactor lies within the bioreaction itself. The nature of the reaction is normally non linear, non stationary and time varying and therefore unpredictable. Unfortunately, in order to obtain controlled conditions of the process parameters such as temperature, pH and production rate, accurate description of the process dynamics is required.

One approach to this class of problem is to introduce adaptive optimization scheme which automatically adjust the inputs for process optimization. This system offers significant potential benefits for difficult process control problems where the process is poorly understood or changes in unpredictable ways. There are several advantages for utilizing the dynamic model identification compared to the steady state identification approach. The advantages are:

(1) An accurate model of the microbial growth is not necessary.

(2) Disturbances and time varying parameters are accounted for by updating the parameters on-line, thus providing an adaptive element; and no need to wait for steady state after each change in the manipulated variables.

(3) It is only an one shot experiment, compared to several operations that need to be done in steady state optimization.

Optimization

Dynamic model identification and optimization combines a classical gradient optimization technique with on-line model identification algorithm. The objective of the optimization analysis is to determine the optimum conditions for the partial cell recycle bioreactor to a predefined objective function (index of performance). The optimum biological condition for this partial cell bioreactor is defined in term of maximum volumetric productivity while on the other hand, several other conditions should be met such as high substrate (glucose) utilization and high concentration of the product (ethanol). The objective function is usually a function of input vector ($\underline{u}$) and the output vector ($\underline{y}$):

$$J = IP = f[\, \underline{u}, \underline{y}(\underline{u}) \,] \qquad (1)$$

Typical input (manipulated) variables for the continuous cell recycle bioreactor are the dilution rate ($D=F_o/V$), initial substrate (So), temperature (T), pH, and may be recycle rate :

$$\underline{u}^T = (D, So, T, pH, R) \qquad (2)$$

Typical output variables are cell (X), substrate (S), and product (P) concentrations :

$$\underline{y}^T = (X, S, P) \qquad (3)$$

The most important information in this optimization work is the gradient vector, ∇G. Which is the change in the objective function due to the change in the input vector. The optimization equation based on this gradient information is as follows:

$$\underline{u}(N+1) = \underline{u}(N) + Q \nabla G \qquad (4)$$

where Q is a positive definite matrix and ∇G is given by:

$$\nabla G = \delta G/\delta \underline{u} + [d\underline{y}/d\underline{u}]\, \delta G/\delta \underline{y} \qquad (5)$$

Recursive Estimation

In order to implement the optimization algorithm in real time, the parameters of the model must be estimated on-line. Algorithms that are suited to real time usage and are based on successive updating the model parameters are called recursive. There are a large number of recursive identification in the literature, the most popular technique is the recursive least squares (RLS). To demonstrate how the algorithm for RLS parameter estimation is used, the single input-single output (SISO) case will be considered.

$$y(k) = \underline{x}^T(k)\underline{\Theta} \qquad (6)$$

where:

$$x^T(k) = [-y(k-1), \ldots -y(k-n), \ldots\ldots, u(k) \ldots, u(k-m), 1] \qquad (7)$$

$$\Theta^T = [\, a_1, \ldots a_n, b_o \ldots b_m, c] \qquad (8)$$

n and m for the above equation determine the model order.

The parameter estimation problem is to find the estimates (Θ) of the unknown parameters which minimize the loss function:

$$JJ = \sum_{t=1}^{nd} (y(t) - \hat{y}(t))^2 \qquad (9)$$

where $\hat{y}$ is the predicted value of the output based on Θ (the predicted value of the parameters). Here, y is the actual value of the output, and n_d is the number of data points.

To get the value of steady state gain of the SISO process, the following equation is necessary:

$$\frac{dy}{du} = \frac{b_o + b_1 + \ldots\ldots + b_m}{1 + a_1 + \ldots\ldots + a_n} \qquad (10)$$

Where the a's and the b's are solved by using the following formulas:

$$\Theta = PX^T\underline{y} \qquad (11)$$

$$P = (X^TX)^{-1} \qquad (12)$$

where P is called the covariance matrix of the estimation error (dimension (n + m + 1) x (n + m + 1)). In order to start the estimation, it is necessary to have equation (12) which is called a one shot algorithm where it uses a complete set of data.

$$X = \begin{bmatrix} \underline{x}^T(i) \\ \underline{x}^T(i+1) \\ \cdot \\ \cdot \\ \cdot \\ \underline{x}^T(i+j) \end{bmatrix} \qquad y = \begin{bmatrix} y(i) \\ y(i+1) \\ \cdot \\ \cdot \\ \cdot \\ y(i+j) \end{bmatrix} \qquad (13)$$

One of the advantages of having a recursive formula for on-line estimation is to reduce the memory of computational requirements. In order to maintain the sensitivity in the process parameter variation, it is advisable to weight new data more heavily than the previous data. This can be done by adding an exponential weighting factor (called a forgetting factor) in the estimation. The addition of forgetting factor results in the following recursive least square algorithm:

$$\Theta(k+1) = \Theta(k) + \psi(k+1)P(k)\underline{x}(k+1)\,[y(k+1) - \underline{x}^T(k+1)\,\Theta(k)] \tag{14}$$

$$P(k+1) = 1/\lambda\,[\,P(k) - \psi\,(k+1)P(k)X^*(k+1)X^{*T}(k+1)P(k)\,] \tag{15}$$

$$\psi(k+1) = 1/\,[\,1 + \underline{x}^T(k+1)P(k)\underline{x}(k+1)\,] \tag{16}$$

where X^* is a $(n + m + 1)^*(n + m + 1)$ square matrix given

by:

$$X^*(k) = [\,\underline{x}(k)\ \underline{0}\ \underline{0}\ \dots\ \underline{0}\,] \tag{17}$$

The value of the forgetting factor (λ), is usually in the range from zero to one. If the forgetting factor is less than one, less weight is given to the previous data estimate.

Simulation Studies

The study was done on the optimization of volumetric productivity of ethanol. Dilution rate was treated as input , ethanol production as well as recycle rate were output parameters. The above optimization procedure, Figure 1 was based on the work of Rolf and Lim (1984).

During the start-up of the estimator, it is desirable that satisfactory estimates be generated before the adaptive optimization is implemented. Thus, the parameter estimation must be initialized properly to obtain good initial estimates and ensure convergence.To trigger the routine one shot algorithm was used on initial set of data

In addition, persistent excitation is also necessary in the process to generate good estimate of the parameters. The type of perturbation signal that is common for this purpose is a pseudo random binary sequence (PRBS).

Experimental Set up

The experimental system for future work is currently under development. As shown in Figure 2, the partially completed process system is consisting of a cell recycle bioreactor, data acquisition unit and a microcomputer. The laboratory scaled bioreactor will be operated using an interactive software to provide facilities for automatic start up, operation and shut down.

Modifications are being made on the currently available bioreactor to suit the requirement. Sensors which among others include temperature, pH, flow and concentration measurement units are being installed. Signals from these units will be amplified and sent through the interface board to the computer. The interface boards are connected directly to the internal PC bus to increase cost, speed and space efficiency.

On completion of this hardware system, actual fermentation experiment will be carried out. Adaptive model developed from the data collected on-line will be optimized. Control actions will then be determined by the computer to achieve optimum process operation.

Results and Discussion

The result of the simulation studies has proved the dependability of the routine. Figure 3 to 10 show the overall result of the run. The optimization curve of the process and the estimated model are shown in Figure 3 and Figure 4, where the maximization of the Function J occur at 350 hour. At this optimum condition the volumetric productivity is 400 g/L/hr (Figure 5) and ethanol concentration at 35 g/L (Figure 8). The recycle rate (Figure 6) of the process is very high, nearly one indicating all the cell is being recycled back to the bioreactor. This behavior is necessary, in order to sustain the production of ethanol at a very high dilution rate. (Figure 10)

Comparing Figure 6 with Figure 7 and Figure 8 with Figure 9 the RLS identification and estimation technique, estimated the output variable very well due to the predicted values having the same trend with the process reaction curve.

The next step for this study is to implement the adaptive optimization package developed here to the actual experimental system. It is believed that the outcome will be favorable. However, certain amount of tuning and operational experience with parameter estimation algorithms is required to make them successful, since certain operational problems may occur during implementation, due to the real world conditions.It should be noted that small model errors can lead to large parameter changes, causing oscillation in the process variable. Fortunately, such excitation of the system will lead to improved estimation, followed by improved optimization. Anderson (1985) has shown that the bursting phenomena can result from noise or unmodeled dynamics in the persistent excitation, quite apart from the estimator windup effect.

Another particular difficult problem in the estimation occurs when a set point change is implemented in a nonlinear system. If during this time unmeasured disturbance suddenly changes. a sudden jump change to the estimated model parameters will occur. This phenomenon has been observed by many investigators, e.g., Vogel and Edgar (1982).

References

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Vogel,E.F. and Edgar,T.F., (1982)." Application of an Adaptive Pole Zero Placement Controller to Chemical Processes with variable Dead Time." Proc. Amer. Control Conference., Arlington, VA. p 536 (June 1982).

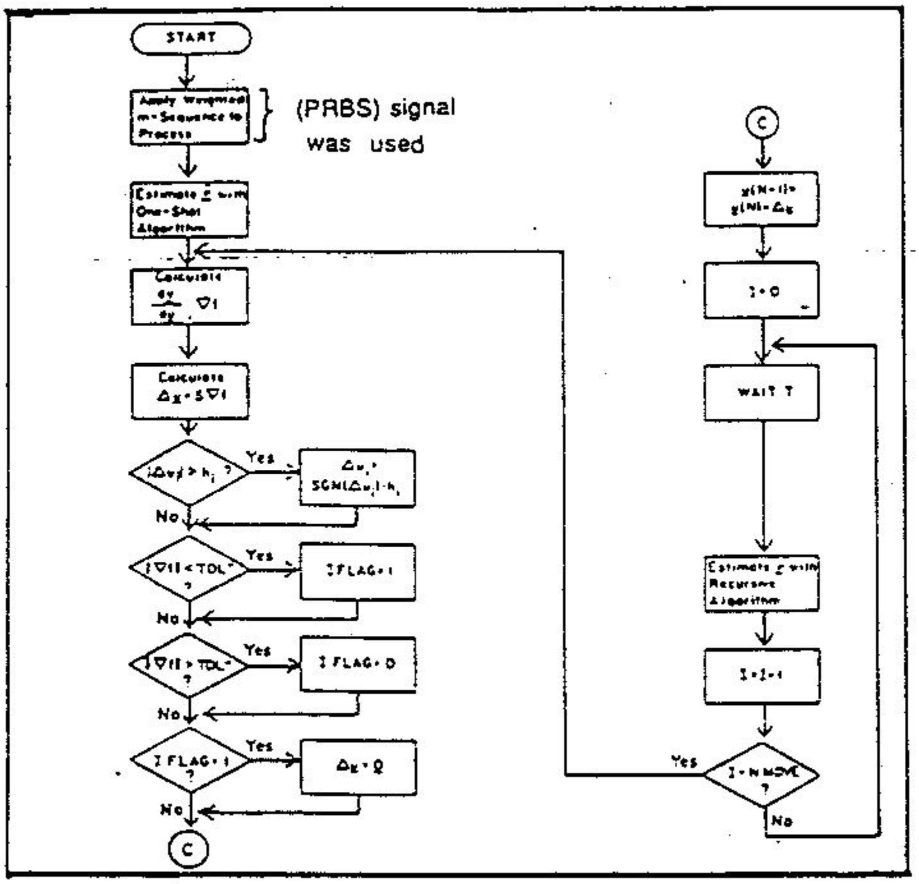

Figure 1

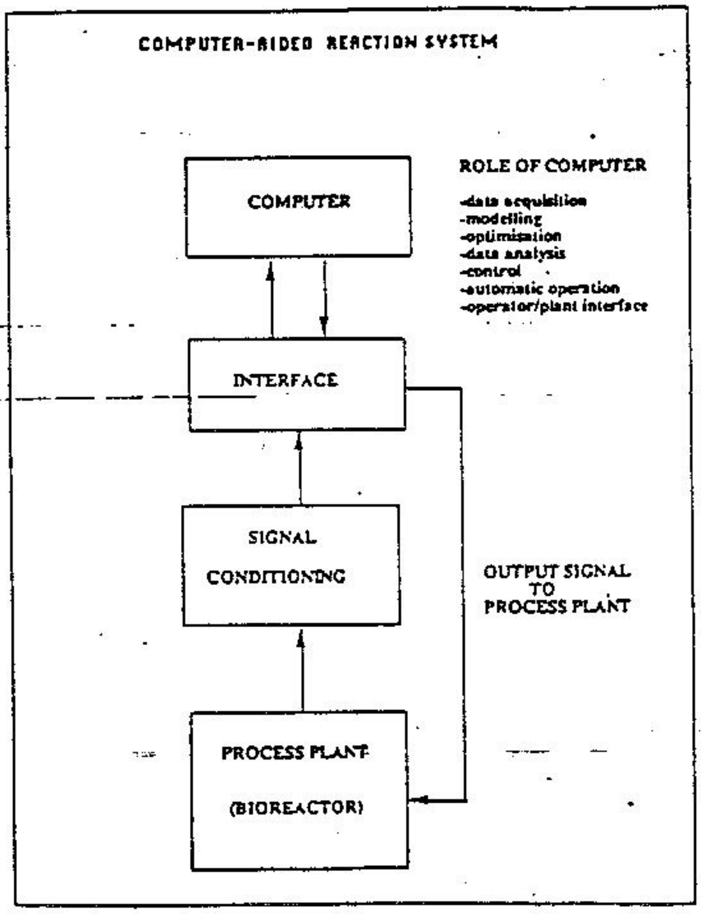

Figure 2

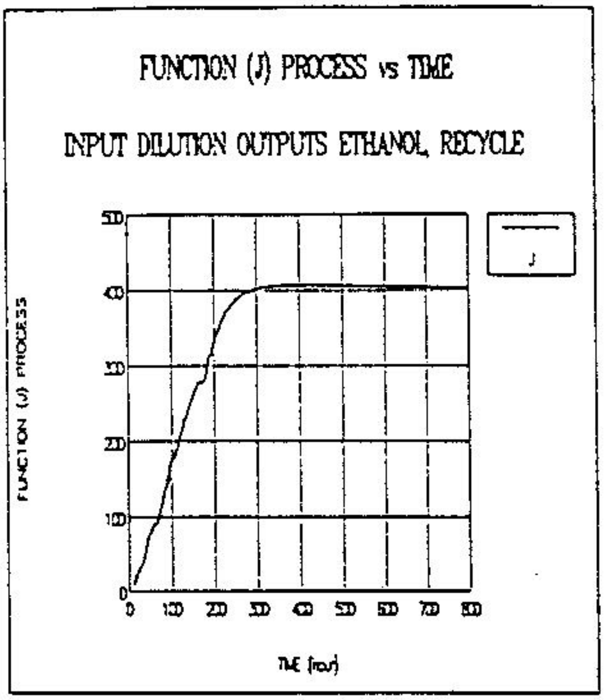

Figure 3

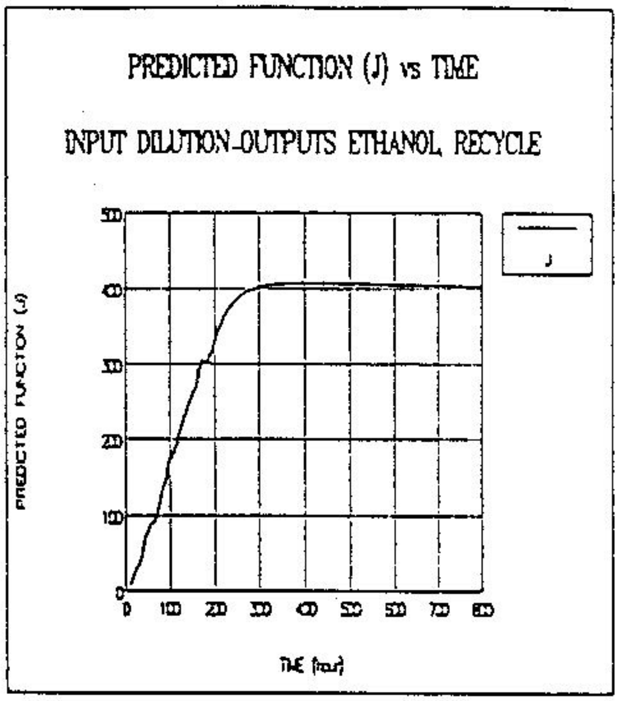

Figure 4

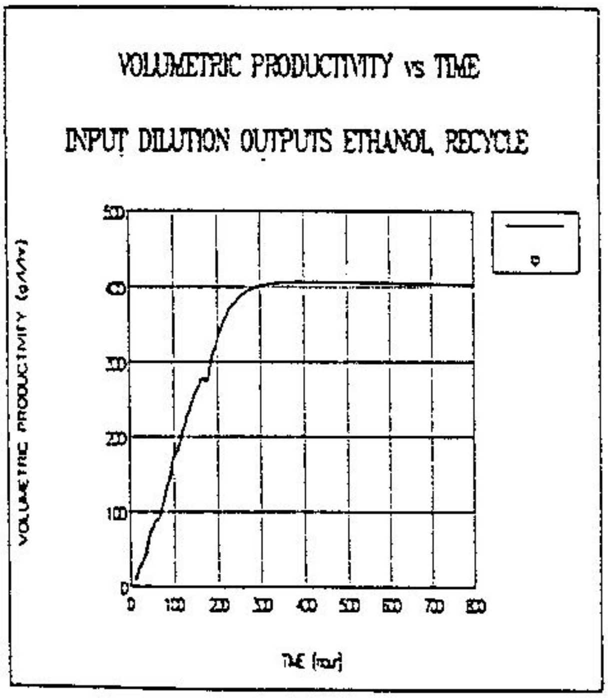

Figure 5

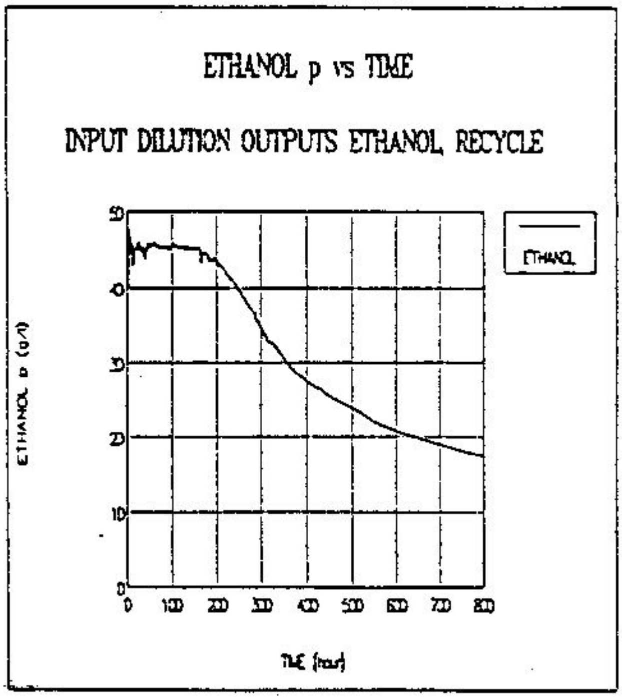

Figure 6

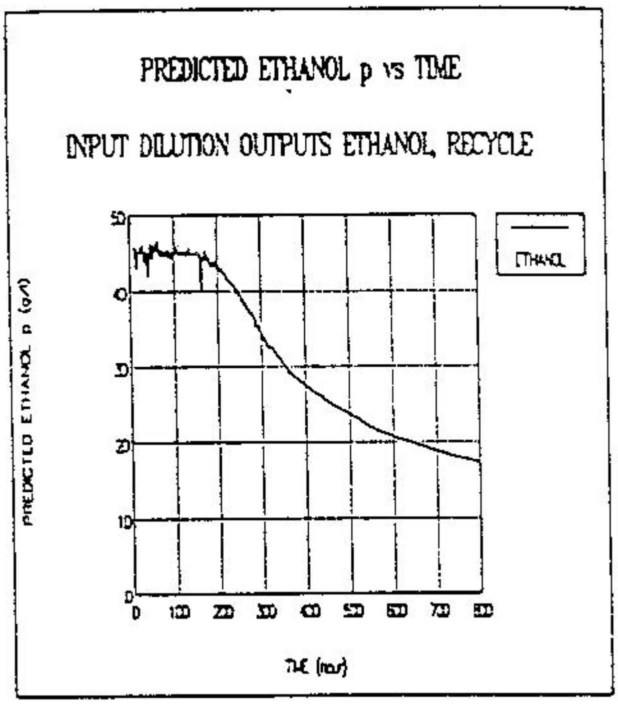

Figure 7

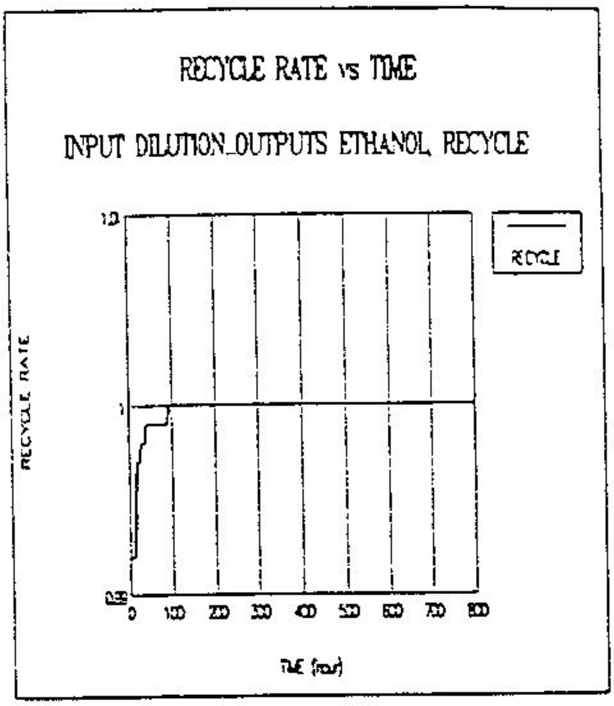

Figure 8

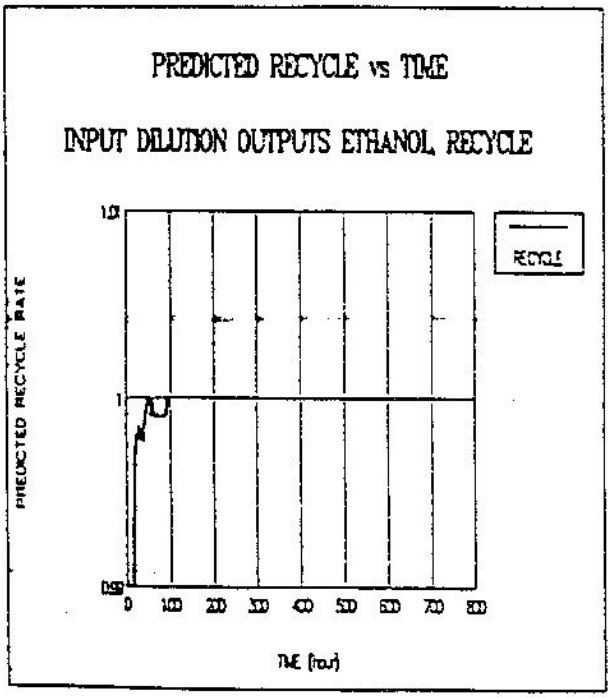

Figure 9

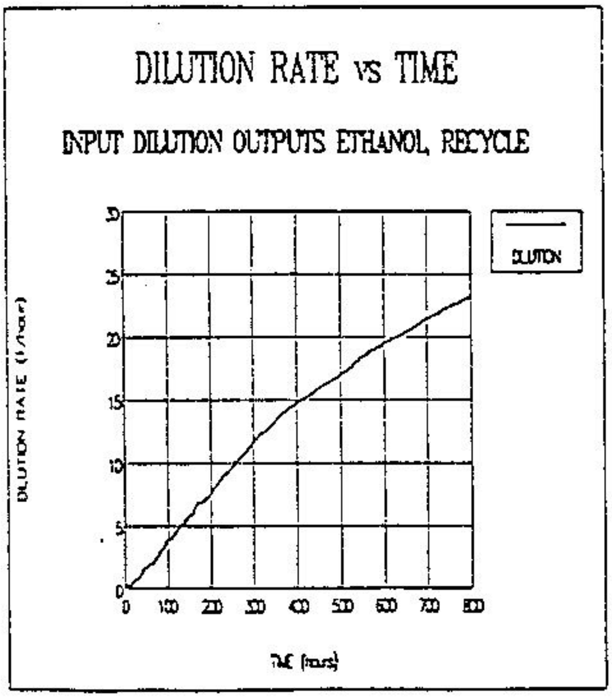

Figure 10